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Towards a Federated Learning Approach for Branched Wired Networks Prognosis

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Abstract—Cable prognosis approaches are necessary to monitor the health state of branched wired networks. Physical failure models are often applied first as a means of monitoring, but their complex production is limiting. To address this limitation, data-driven ones are among the most suitable approaches. This is because sensors can provide a significant amount of condition monitoring data that can be used to estimate the remaining useful life of wired networks. This paper explores the uses of machine learning and distributed reflectometry sensors in establishing the guidelines for the implementation of a wired network prognosis strategy. After realizing a reflectometry diagnosis, the acquired signals are processed to extract features that are representative of cable degradation. Then, machine learning models are used to forecast the evolution of the features for the purpose of quantifying the future global degradation state of the wired network. Finally, the remaining useful life of the wired network is estimated with this quantification and an end-of-life threshold. The next step of this project is to test the efficiency of the strategy proposed here, proving the suitability of guidelines based on data-driven models, as well as the practicality of developing a federated learning solution that addresses data quantity and privacy issues.

Index Terms—Prognostics and health management, cable aging, reflectometry, remaining useful life, data-driven, federated learning

I. INTRODUCTION

Nowadays, wired networks are ubiquitous in many sectors such as modern automotive, aeronautics, nuclear power plants, or power distribution. These networks are usually operating in severe environments (e.g. mechanical, chemical, thermal stresses) which can cause them important damages such as chafing, heating, bending radius, etc. Consequently, they become less efficient and less reliable. For safety and economic reasons, it is necessary to repair or replace cables before they are no longer in working order. As it contributes to Predictive Maintenance (PdM), which consists of anticipating future system failures, it corresponds more precisely to determining the proper time to replace cables. A health state prognosis method may be a solution that meets these requirements since it would allow, for instance, to optimize maintenance planning, ensure cable performance, or anticipate breakdowns.

Once the main challenges are identified, our goal is to develop a cable condition monitoring strategy to supervise the health state evolution of the wired networks and estimate their Remaining Useful Life (RUL). RUL corresponds to the period from the current time to the end of the useful life [1]. Such an approach is part of the Prognostics field of the research domain of Prognostics and Health Management (PHM). PHM is an engineering discipline that aims at providing users with an integrated view of the health state of a machine or an overall system [2]. Prognostics concerns the study and prediction of the future health evolution of the system which is monitored, through the estimation of the RUL [3].

Literature presents several methods that permit monitoring the health state of a system by performing its prognosis [2], [3], [4]. They are divided into four categories: model-based approaches (also referred to as physics-based) that concern mainly multi-physics models for asset normal operation and physical degradation laws [5]; data-driven approaches that are based on condition monitoring data [1], [6], [7]; knowledge-based approaches that rely on expert judgments or expert rules; and hybrid approaches that represent combinations of the three previous categories.

In the cable diagnosis domain, reflectometry-based sensors are implemented in the wired network under test in order to detect and locate the appearance of defects. The main idea is to inject a test signal down to the network and to analyze the reflected signal in the presence of defects. Although reflectometry allows to establish a cable diagnosis, it does not permit to ensure the cable prognosis and hence, to estimate its RUL. In this context, this paper presents the guidelines established in the first year of this Ph.D. project that aims to study a

new strategy based on a machine learning approach and distributed reflectometry-based sensors for wired network prognosis.

First, section II explains the issues related to prognosis in the context of cable aging. This section introduces our motivations for this project and the problem statement. Then, our prognosis methodology will be detailed in section III and several challenges will be mentioned. Finally, section IV focuses on the data and the generation of a dataset, which is followed by a conclusion in section V.

II. CABLE AGING & PROGNOSIS ISSUES

As mentioned in section I, failures can appear within wired networks due to their environmental conditions (e.g. chemical processes, temperature, pollution, humidity, and corrosion) and their usage profile (e.g. overload, overvoltage, electrical trees). In addition, the physical interactions to which they are subjected in the system (chaffing, vibration, tension, torsion, human handling of cables) can also impact their health condition. In most cases, these damages represent progressive soft faults (chafing, crushing, hole) that do not interrupt the energy or data transmission but can evolve under those operating and environmental constraints to hard faults (i.e. open-circuit or short-circuit). These faults can lead to a system malfunction requiring reactive maintenance at significant financial costs and delays.

Cable aging can be influenced by many factors and we propose firstly to study a few of them. According to existing research in the scientific literature [8], [9], [10], the main degradation process of a cable seems to be related to its insulation. As far as we know, there is no complete physical law that describes cable insulation degradation, but we can suppose that the chemical, mechanical and electrical properties of the insulation material continuously change during the process of thermal aging [11]. This type of stress can be found in several applications like nuclear power plants, civil aircrafts, or in the space field. The insulation is characterized by its relative permittivity noted ϵ_r .

To monitor cable insulation aging, physics-based methods can be used by developing a degradation model that describes the evolution of the cable health state [12]. However, it is difficult to describe such a physical model due to a lack of information about the cable insulation aging mechanism. Physics-based approaches typically need a physical failure model to estimate the RUL, which in most practical scenarios, is challenging to produce. Moreover, knowledge-based methods are not relevant because it usually relies, for the cable diagnosis, on a one-shot observation made by the expert and therefore cannot be automated. Data-driven methods seem to be the best choice to predict the evolution of the health status of a wired network as we can collect real condition monitoring data during its useful life. This type of data is also referred to as condition indicators, which is defined as a feature of condition monitoring system data that changes in a predictable way as the system degrades [3].

In terms of existing data-driven works, there are several works related to cable prognosis and RUL estimation which use non-destructive, non-intrusive, and online diagnostic techniques. Liu et al. [13] propose an online automated data-driven prognosis method for underground cables based on voltage and current field data. The cable RUL is forecasted with a sliding-window regression method; it predicts the time for the cumulative effect of the selected features to reach the threshold. Aizpurua et al. [14] present a novel cable lifetime estimation framework that connects data-driven probabilistic uncertainty models with physics-of-failure-based operations. The cable lifetime estimation is performed by a particle filter method. Wang et al. [15] introduce a prognostic approach that integrates Joint Time-Frequency Domain Reflectometry (JTFDR), Continuous Wavelet Transform (CWT), and particle filter to estimate the degradation of insulation and predict the remaining useful life of coaxial cables.

These existing data-driven methods are relevant for cable prognosis, but they present some limitations. First, they make a direct estimation of the RUL that requires to have access to labeled data. Considering the long degradation process of cables and the challenging data acquisition process, the RUL labels can only be accessed when cables are no longer in working order. So, the new sensor measurements cannot be used to update and improve the forecasting model as the acquisitions are made. Second, they do not provide an interpretable prediction of the wired network health state as they only estimate its RUL. To deal with these two limitations, we propose a different approach by forecasting the evolution of the extracted features (i.e. the inputs of our forecasting models) using ML algorithms. Indeed, selecting a state-of-the-art Machine Learning method instead of sliding-window regression or particle filter methods can also improve the accuracy of the prognosis. However, forecasting the features instead of the RUL requires adding a degradation state quantification step to finally estimate the RUL. This step will also be considered in our prognosis methodology.

III. PROGNOSIS METHODOLOGY

Based on these motivations, a new wired network prognosis methodology is proposed as the main contribution of this paper. Composed of five key steps, it explains how the raw signals will be processed to estimate the RUL, Fig. 1. Those referred steps are shown in the following subsections. Subsection III-A presents the monitoring technique we have chosen and the way raw signals are collected. Subsection III-B focuses on the transformation of raw signals into relevant features that are representative of cable degradation. Subsection III-C introduces machine learning methods already used in PHM works. After specifying their limitations, we highlight the need for a distributed learning method to achieve such an efficient prognosis. Subsection III-D explains the interpretation of these predicted features which is done through a global degradation state quantification. Subsection III-E describes the RUL estimation process that needs to be done from the global indicator.

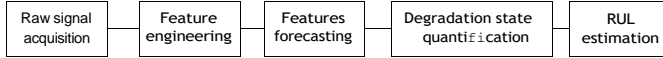


Fig. 1. Wired network prognosis methodology.

A. Cable condition indicators & Raw signal acquisition

First, to monitor the health state of wired networks and so the cable degradation, condition indicators are required. They can be obtained by performing a cable diagnosis, i.e. getting information about the health and performance of cables and their insulation. Several cable condition monitoring techniques are commonly used for such purposes. For instance, Auzanneau [16] presents the most basic methods, e.g. visual inspection, x-rays, ultrasound-guided wave, infrared thermal imaging, continuity measurement, and reflectometry. Furse et al. [17] review the state-of-the-art about the detection, location, and diagnosis of faults in electrical systems. They cite voltage, current, and power sensing; acoustic-based methods; capacitance and inductance measurements; and make a complete description of the existing reflectometry methods. Toll et al.

[18] cite techniques that are successfully used in nuclear facilities. They present for example dielectric spectroscopy, elongation at break, indenter modulus, and also reflectometry. All these techniques have their advantages and drawbacks such as being in-situ, non-destructive, and working for specific polymers or cable configurations.

Reflectometry [17], [16] is a method that permits detecting, localizing, and characterizing the fault over the entire length of a wired network. For a point-to-point transmission line, a high-frequency electrical signal is injected at an extremity and propagates through the transmission line. A part of the signal is reflected when an impedance discontinuity is present, and the reflectometry response can be obtained by measuring these reflected signals. The reflectogram highlights any type of defect in the form of a specific signature. Hard faults are easy to locate, but soft faults are more or less detectable according to their severity levels. For a wired network, if we monitor the system with only one access point, there is an ambiguity in the localization of the fault, i.e. we can't determine the branch where the fault is located. Distributed reflectometry

[19] tackles this issue by injecting multiple signals with good auto-correlation properties (like M-sequence) at multiple network access points.

Considering the limitations of the other techniques, reflectometry seems to be the most suitable one to determine the health state of branched wired networks as it is a non-destructive, non-intrusive, and online monitoring method that can be used on the most common cable types. It can also assess and quantify the insulation damage that can appear in a wired network. Moreover, this method does not require full access to the wired network, and we can embed it in the operating system.

In this paper, the reflectometry method will be used to get condition indicators about the wired networks. For all diagnostic measures, we inject predefined signals to the access points, also defined as sensor nodes which can be the ends of the branches of a wired network. Then, we acquire the reflected part of the signals from each sensor node. The Orthogonal Multi-tone Time Domain Reflectometry (OMTDR) will be selected thanks to its capability to control the bandwidth which ensures, not only online, but also distributed diagnosis [20]. In this case, a correlation step between the incident signal and the reflected signal is also performed to compute the reflectogram. An example of a Y-shaped wired network is shown in Fig. 2 with its associated reflectogram in Fig. 3. Each diagnostic

measure, which will be carried out at regular times throughout the useful life of the cable, will produce one reflectogram per sensor node to cover the entire wired network.

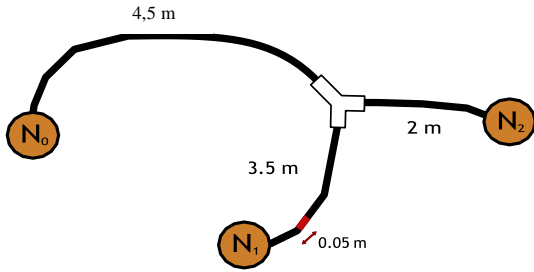


Fig. 2. Y-shaped wired network with a 5 cm soft fault positioned on the branch of length 3.5 m.

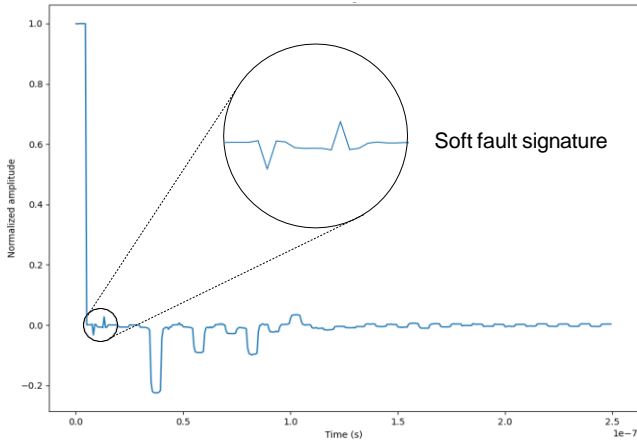


Fig. 3. Reflectogram acquired from the sensor node N_1 of Fig. 2. An OMTDR signal has been injected into N_1 . The load impedance of the other nodes, i.e. N_0 and N_2 , are matched with the characteristic impedance of the transmission line. The signature of the soft fault, i.e. a succession of two peaks of opposite amplitude, can be found at the zoom level.

B. Feature engineering

Once the diagnostic measure is performed, the second step consists of extracting several features from the reflectograms to have more representative information on the cable degradation. The condition indicators provided by the reflectometry diagnosis are therefore processed to be improved. They must be formalized as they depend on expert knowledge and have to follow some desired characteristics, e.g. monotonicity, robustness, and adaptability [21]. This process is called Feature Engineering, a manual pre-processing to derive more valuable representations of signals in the data [3]. Once the extraction of these features is defined, it should be automated so that it can be integrated into the prognosis system.

The definition and the selection of the most representative condition indicators of cable degradation from the reflectograms are quite challenging. Our first proposal is to localize and follow any impedance discontinuity in the reflectograms by extracting their amplitude and their temporal width. Another example of a feature could be a mean squared error computed on the difference between the first reflectogram (diagnostic at $t = 0$) and the actual reflectogram (the last obtained reflectogram) in the area of the fault; this difference is called differential reflectogram. Potential issues may appear during this process due to the complexity of the reflectograms analysis in the case of complex wired networks (e.g. presence of round-trip peaks or junctions). Moreover, we will vary the definition of the features and study, for each case, the accuracy and the sensitivity of the forecasting model, which will be presented in the next step III-C. The initial definition of the features will probably evolve by

following a reverse- engineering process according to these results.

Therefore, by analyzing the evolution of these features, we can monitor the evolution of the previously localized discontinuities.

C. Features forecasting

The third step is to use a data-driven method to forecast the evolution of the extracted features by using their historical values. Such prediction allows to calculate, explained in the following step III-D, the future global degradation state of the wired network. The choice of using a data-driven method is motivated by the fact that these methods are becoming more and more popular for many years in the research domain of PHM.

Although this paper only deals with the problem of cable prognosis, the features forecasting problem can be extended to more generic research works. According to the application, the condition indicators will not be the same, but the goal remains to establish the relationship between these indicators and the corresponding RUL. Moreover, the fact of counting with multiple and sequential time series features makes this work a multi-variate time series forecasting problem. This means we can select and use existing multi-variate time series forecasting methods applied to PHM to solve our research problem.

1) *Current state about Machine Learning*: Among the most commonly used methods [1], [6], [7], Machine Learning (ML) approaches seem to be the best choice to learn the mapping from the features to the associated RUL. Neural network- based approaches are especially relevant candidates as they have the advantage of modeling this mapping without prior expertise on the physical behavior of the system. Moreover, different kinds of data can be directly used as deep learning model inputs, such as raw sensor data or extracted features. For instance, Nuhic et al. [22] present an application of a Support Vector Machine (SVM) algorithm to estimate the state of health of Lithium-ion batteries. Guo et al. [23] define a feature extraction method and use a Recurrent Neural Network (RNN) to make RUL predictions. Zheng et al. [24] introduce a Long Short-Term Memory (LSTM) approach for RUL estimation and applies it to several benchmarking PHM problems such as the NASA's turbofan engine degradation one [25]. This popular dataset contains simulated data produced by a model-based simulation program called Commercial Modular AeroPropulsion System Simulation (C-MAPSS). Li et al. [26] propose a deep convolution neural network for prognostics that outperforms the other existing methods on the C-MAPSS dataset.

These methods constitute a starting point for wired network features forecasting. In our particular case, all the features from each sensor node of the wired network are regrouped and considered inputs of a single forecasting model. An alternative approach would have been to have one forecasting model per sensor node and aggregate the outputs at the end of the different predictions. However, this second approach makes the prediction task more challenging since the models will have fewer inputs, and therefore less information about the degradation of the wired network.

2) *Limitations*: Besides the advantages of ML approaches, they also come with limitations as requiring a large amount of data to perform an accurate prognosis. The study of a single wired network will not be sufficient to develop an accurate ML model as these models learn from previous failures to predict the health state evolution of a system. Indeed, branched wired networks do not fail so frequently to have enough training data. For this reason, a dataset that tracks the health status of several wired networks over their useful life is required. We can solve this problem by learning from a dataset built from a cluster of wired networks with similar working conditions or specifications, i.e. topology or type. However, a centralized grouping of condition monitoring data is not feasible in a realistic environment where data are owned by several entities and are confidential. Moreover, in terms of communication costs, this amount of data can also be expensive to transmit depending on the chosen diagnostic frequency.

3) *Federated Learning trends*: To tackle this privacy challenge, Federated Learning (FL), a distributed machine learning paradigm introduced by McMahan et al. in 2016 [27], is used. In this method, many clients, e.g. mobile devices or organizations, collaborate under the command of a server while keeping the training data decentralized. Each client performs its model training locally, then sends the model parameters to the server and, finally, the server aggregates those client parameters to constitute a global model. FL was initially formalized by the Federated Averaging algorithm (FedAvg) [27], in which the aggregation is a weighted average. As this field evolves, FL could be categorized into horizontal and vertical FL according to data distribution characteristics among the connected clients. Horizontal FL represents the scenarios in which the clients' training data share the same feature space but have different sample spaces, whereas vertical FL represents the opposite scenario. However, FL models have limitations; they usually have lower accuracy than models trained by a standard centralized algorithm, specially when training data are not

independent and identically distributed (non-iid). To overcome this problem, many FL research problems are currently being explored [28], [29], [30].

These research works are also focused on preserving user data privacy and securing the system against potential attacks.

In this project, FL will be applied to the PHM domain. The FL configuration associated with this domain is generally a cross-silo horizontal federated learning. Some work related to these two fields has already started. Dhada et al. [31] apply FL as a solution to the distributed data sources of industrial assets bound by privacy policies. FedAvg is used on an RNN for predicting simulated turbofan fleet failures with the C-MAPSS dataset. Rosero et al. [32] compare distributed collaborative learning techniques for PHM systems on the same dataset. They use feed-forward neural networks on centralized and decentralized scenarios to compare the prediction error minimization of FL algorithms such as FedAvg and Federated Proximal Term (FedProx). Bemani et al. [33] propose a federated SVM and a federated LSTM for RUL estimation. The authors have also evaluated these models on the C-MAPSS dataset. Guo et al. [34] introduce a federated learning-based RUL prediction method named FedRUL. A global encoder is set up in a server with an FL strategy and then sent back to the clients. These global models are combined locally with decoders, which constitute convolutional autoencoders. Then, features are extracted thanks to these autoencoders and are sent to the server to train an RUL predictor. Finally, this one is distributed to each client for implementing corresponding RUL prediction tasks.

This paradigm, which has proven to be effective in a few examples of PHM, could allow our method to be viable and to learn from multiple sources of data while keeping the data confidential.

D. Global degradation state quantification

According to [3], for monitoring the system health condition, it is recommended to combine all the condition indicators into only one health indicator. This way, the end user will be able to exploit this unique indicator that represents the global health state of the system. In our context, once the model predicts the evolution of the extracted features, the evolution of a unique health indicator of the wired network is quantified from these predictions. This unique indicator is also called the global degradation state.

Moreover, this quantification will simplify the implementation of the RUL estimation step by only setting up one threshold. However, it is necessary to pay attention to the uniformity of the quantification so that two wired networks with the same level of degradation but different values of features will be associated with the same global degradation state. For the moment, no solution has been considered for this quantification step since efforts are primarily focused on the previous step, i.e. features forecasting III-C.

E. RUL estimation

Finally, the RUL will be estimated with an end-of-life threshold and the global degradation state quantification that has been previously computed. The end-of-life threshold needs to be set up according to the use case relying on the initial conditions, the asset experts, and maintenance professionals. Two general research questions arise from this step: what is the end-of-life criterion of a cable? How can the end-of-life threshold of a wired network be precisely determined?

IV. DISCUSSION ABOUT DATA PREPARATION

As data-driven approaches and specially ML have been chosen to forecast the features, it requires data to train and validate the models. In the context of cable prognosis, data accessibility is a real issue nowadays. It is not possible acquiring data on the total lifetime of cable aging from the industry and no public dataset related to cable aging was found. Therefore, this work studies how to build an efficient wired network prognosis relying on the fact that obtaining or constituting a consistent dataset is challenging. The studied systems are wired networks with a non-complex topology (Y-shaped networks) composed of coaxial cables RG58, e.g. Fig. 2. Local thermal stress will be applied to these networks at the level of an incipient fault in order to analyze their degradation. Moreover, variety is added to the data by studying several topologies of Y-shaped networks with different branch sizes and a fault positioned at different locations. For further validation, Y-shaped networks can be replaced by more complex wired networks composed of a different type of cable.

To constitute a first dataset, we have decided to simulate reflectograms. Our dataset is composed of multiple reflectograms that follow the health state evolution of several wired networks with different topologies. For each of these wired networks, a time interval was defined and segmented to associate each timestep to his corresponding reflectogram. This association is made possible by the integration in the simulator of a simple linear degradation law of the dielectric constant [10], [15] that acts as cable thermal stress. Each point of this

degradation law is injected at the inputs of the simulator to produce the associated reflectogram. In addition, the simulator is initialized by indicating information about the wired network characteristic (e.g. number of branches, their length, physical parameters of the cables) and additional information about the reflectometry method used (e.g. OMTDR parameters). However, these simulated reflectograms are not very faithful to real cable aging because the degradation law is too approximate.

Cable aging experiments can be performed to have a more precise representation of this mechanism. Because of the long lifetime of the studied cables, it will not be possible to carry out normal aging experiments during this work. Indeed, the degradation process of cables takes place over decades, depending on the application. But, we can consider performing thermal accelerated aging experiments thanks to a cable aging test platform of our laboratory. Experimentation will involve localized accelerated aging tests, i.e. only a specific part of the wired network will be aged. An incipient fault will be created and the goal will be to monitor its evolution while it is confronted with thermal stress.

V. CONCLUSION

Through this position paper, a methodology has been defined to address the cable prognosis challenge. Currently, in this Ph.D. project, the first efforts focus on defining the most representative indicators of cable degradation and the data-driven forecasting of these features. As the steps of this method follow one another, the global degradation state quantification and the RUL estimation will be explored in a second term. In addition, difficulties with dataset construction have been

identified, which is a problem as a consistent dataset is required to ensure an accurate ML prognosis. The accelerated aging experiments that are being conducted are our solution to generate a more relevant dataset, and FL has been selected as a promising method to make the method more viable in a real context. Our next steps will therefore focus on the integration of FL in this cable prognosis method, and also on the extension of this method to other applications areas, as for example to the NASA's turbofan engine degradation prognosis usecase.

REFERENCES

- [1] X.-S. Si, W. Wang, C.-H. Hu, and D.-H. Zhou, "Remaining useful life estimation – A review on the statistical data driven approaches," *European Journal of Operational Research*, vol. 213, no. 1, pp. 1–14, Aug. 2011.
- [2] J. Lee, F. Wu, W. Zhao, M. Ghaffari, L. Liao, and D. Siegel, "Prognostics and health management design for rotary machinery systems—Reviews, methodology and applications," *Mechanical Systems and Signal Processing*, vol. 42, no. 1-2, pp. 314–334, Jan. 2014.
- [3] O. Fink, Q. Wang, M. Svensen, P. Dersin, W.-J. Lee, and M. Ducoffe, "Potential, challenges and future directions for deep learning in prognostics and health management applications," *Engineering Applications of Artificial Intelligence*, vol. 92, p. 103678, Jun. 2020.
- [4] O. Fink, "Data-Driven Intelligent Predictive Maintenance of Industrial Assets," in *Women in Industrial and Systems Engineering*, A. E. Smith, Ed. Cham: Springer International Publishing, 2020, pp. 589–605.
- [5] T. Tinga and R. Loendersloot, "Physical Model-Based Prognostics and Health Monitoring to Enable Predictive Maintenance," in *Predictive Maintenance in Dynamic Systems: Advanced Methods, Decision Support Tools and Real-World Applications*, E. Lughofer and M. Sayed-Mouchaweh, Eds. Cham: Springer International Publishing, 2019, pp. 313–353.
- [6] K. L. Tsui, N. Chen, Q. Zhou, Y. Hai, and W. Wang, "Prognostics and Health Management: A Review on Data Driven Approaches," *Mathematical Problems in Engineering*, vol. 2015, pp. 1–17, 2015.
- [7] G. Prakash, X.-X. Yuan, B. Hazra, and D. Mizutani, "Toward a Big Data-Based Approach: A Review on Degradation Models for Prognosis of Critical Infrastructure," *Journal of Nondestructive Evaluation, Diagnostics and Prognostics of Engineering Systems*, vol. 4, no. 2, p. 021005, May 2021.
- [8] I. A. E. Agency, *Assessing and Managing Cable Ageing in Nuclear Power Plants*. Internat. Atomic Energy Agency, 2012.
- [9] K. Simmons, L. Fifield, M. Westman, J. Tedeschi, A. Jones, M. Prowant, A. Pardini, and P. Ramuhalli, "Determining Remaining Useful Life of Aging Cables in Nuclear Power Plants – Interim Status for FY2014," *Pacific Northwest National Laboratory, M3LW-140R04022*, p. 76, 2014.
- [10] S. Dalal, R. Gorur, and M. Dyer, "Aging of distribution cables in service and its simulation in the laboratory," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 12, no. 1, pp. 139–146, Feb. 2005.
- [11] L. Li, N. Bowler, M. R. Kessler, and S. H. Yoon, "Dielectric response of PTFE and ETFE wiring insulation to thermal exposure," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 17, no. 4, pp. 1234–1241, Aug. 2010.
- [12] S. V. Suraci and D. Fabiani, "Aging Modeling of Low-Voltage Cables Subjected to Radio-Chemical Aging," *IEEE Access*, vol. 9, pp. 83 569– 83 578, 2021.
- [13] S. Liu, Y. Wang, and F. Tian, "Prognosis of Underground Cable via Online Data-Driven Method With Field Data," *IEEE Transactions on Industrial Electronics*, vol. 62, no. 12, pp. 7786–7794, Dec. 2015.
- [14] J. I. Aizpurua, B. G. Stewart, S. D. J. McArthur, N. Jajware, M. Kearns, U. Garro, E. Muxika, and M. Mendicute, "A Diagnostics Framework for Underground Power Cables Lifetime Estimation Under Uncertainty," *IEEE Transactions on Power Delivery*, vol. 36, no. 4, pp. 2014–2024, Aug. 2021.
- [15] X. Wang, E. Liu, and B. Zhang, "Reflectometry based Cable Insulation Aging Diagnosis and Prognosis," *IEEE Transactions on Industrial Electronics*, pp. 1–1, 2021.
- [16] F. Auzanneau, "Wire Troubleshooting and Diagnosis: Review and Perspective," *Progress In Electromagnetics Research B*, vol. 49, pp. 253– 279, 2013.
- [17] C. M. Furse, M. Kafal, R. Razzaghi, and Y.-J. Shin, "Fault Diagnosis for Electrical Systems and Power Networks: A Review," *IEEE Sensors Journal*, vol. 21, no. 2, pp. 888–906, Jan. 2021.
- [18] T. Toll, C. Sexton, B. McConkey, and G. Harmon, "A Cable Condition Monitoring Strategy For Safe And Reliable Plant Operation," in *2020 IEEE Electrical Insulation Conference (EIC)*. Knoxville, TN, USA: IEEE, Jun. 2020, pp. 369–374.
- [19] N. Ravot, "Analyse et diagnostic de réseaux filaires complexes par réflectométrie," These de Doctorat, Paris 11, Jan. 2007.
- [20] L. Incarbono, S. Evain, W. Ben Hassen, F. Auzanneau, A. Dupret, Y. Bonhomme, F. Morel, R. Gabet, L. Solange, and A. Zanchetta, "OMTDR based integrated cable health monitoring system SmartCo: An embedded reflectometry system to ensure harness auto-test," in *2015 IEEE 10th Conference on Industrial Electronics and Applications (ICIEA)*, Jun. 2015, pp. 1761–1765.
- [21] Y. Hu, T. Palme, and O. Fink, "Deep Health Indicator Extraction: A Method based on Auto-encoders and Extreme Learning Machines," in *Annual Conference of the PHM Society*, vol. 8, 2016, p. 8.
- [22] A. Nuhic, T. Terzimehic, T. Soczka-Guth, M. Buchholz, and K. Dietmayer, "Health diagnosis and remaining useful life prognostics of lithium-ion batteries using data-driven methods," *Journal of Power Sources*, vol. 239, pp. 680–688, Oct. 2013.
- [23] L. Guo, N. Li, F. Jia, Y. Lei, and J. Lin, "A recurrent neural network based health indicator for remaining useful life prediction of bearings," *Neurocomputing*, vol. 240, pp. 98–109, May 2017.
- [24] S. Zheng, K. Ristovski, A. Farahat, and C. Gupta, "Long Short-Term Memory Network for Remaining Useful Life estimation," in *2017 IEEE International Conference on Prognostics and Health Management (ICPHM)*, Jun. 2017, pp. 88–95.
- [25] A. Saxena, K. Goebel, D. Simon, and N. Eklund, "Damage propagation modeling for aircraft engine run-to-failure simulation," in *2008 International Conference on Prognostics and Health Management*. Denver, CO, USA: IEEE, Oct. 2008, pp. 1–9.
- [26] X. Li, Q. Ding, and J.-Q. Sun, "Remaining useful life estimation in prognostics using deep convolution neural networks," *Reliability Engineering & System Safety*, vol. 172, pp. 1–11, Apr. 2018.
- [27] H. B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, "Communication-Efficient Learning of Deep Networks from Decentralized Data," *arXiv:1602.05629 [cs]*, Feb. 2017.
- [28] P. Kairouz, H. B. McMahan, B. Avent, A. Bellet, M. Bennis, A. N. Bhagoji, K. Bonawitz, Z. Charles, G. Cormode, R. Cummings, R. G. L. D'Oliveira, H. Eichner, S. E. Rouayheb, D. Evans, J. Gardner, Z. Garrett, A. Gascon, B. Ghazi, P. B. Gibbons, M. Gruteser, Z. Harchaoui, C. He, L. He, Z. Huo, B. Hutchinson, J. Hsu, M. Jaggi, T. Javidi, G. Joshi, M. Khodak, J. Konecny, A. Korolova, F. Koushanfar, S. Koyejo, T. Lepoint, Y. Liu, P. Mittal, M. Mohri, R. Nock, A. O'zgu'r, R. Pagh, M. Raykova, H. Qi, D. Ramage, R. Raskar, D. Song, W. Song, S. U. Stich, Z. Sun, A. T. Suresh, F. Tramer, P. Vepakomma, J. Wang, L. Xiong, Z. Xu, Q. Yang, F. X. Yu, H. Yu, and S. Zhao, "Advances and Open Problems in Federated Learning," *arXiv:1912.04977 [cs, stat]*, Mar. 2021.
- [29] Q. Yang, Y. Liu, T. Chen, and Y. Tong, "Federated Machine Learning: Concept and Applications," *ACM Transactions on Intelligent Systems and*

Technology, vol. 10, no. 2, pp. 1–19, Feb. 2019.

- [30] H. Zhu, J. Xu, S. Liu, and Y. Jin, “Federated Learning on Non-IID Data: A Survey,” *arXiv:2106.06843 [cs]*, Jun. 2021.
- [31] M. Dhada, A. S. Palau, and A. K. Parlikad, “Federated Learning for Collaborative Prognosis,” in *International Conference on Precision, Meso, Micro and Nano Engineering (COPEN 2019)*, IIT Indore, 2019, p. 6.
- [32] R. L. Rosero, C. Silva, and B. Ribeiro, “Remaining Useful Life Estimation in Aircraft Components with Federated Learning,” *PHM Society European Conference*, vol. 5, no. 1, p. 9, 2020.
- [33] A. Bemani and N. Björnsell, “Aggregation Strategy on Federated Machine Learning Algorithm for Collaborative Predictive Maintenance,” *Sensors*, vol. 22, no. 16, p. 6252, Aug. 2022.
- [34] L. Guo, Y. Yu, M. Qian, R. Zhang, H. Gao, and Z. Cheng, “FedRUL: A New Federated Learning Method for Edge-Cloud Collaboration Based Remaining Useful Life Prediction of Machines,” *IEEE/ASME Transactions on Mechatronics*, pp. 1–10, 2022.